BAT Algorithm based Beamforming for mmWave Massive MIMO Systems

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***Abstract*—In this paper, an optimized analog beamforming scheme for millimeter-wave (mmWave) massive MIMO system is presented. This scheme aims to achieve the near-optimal performance by searching for the optimized combination of analog precoder and combiner. In order to compensate for the occurrence of attenuation in the magnitude of mmWave signals, the codebook dependent analog beamforming in conjunction with precoding at transmitting end and combining signals at the receiving end is utilized. Nonetheless, the existing and traditional beamforming schemes involve a more difficult and complicated search for the optimal combination of analog precoder/ combiner matrices from predefined codebooks. To solve this problem, we have referred to a modified Bat Algorithm to find the optimal combination value. This algorithm will explore the possible pairs of analog precoder/ combiner as a way to come up with the best match in order to attain near-optimal performance. The analysis shows that the optimized beamforming scheme presented in this paper can improve the performance that is very close to the beam steering benchmark that we have considered.**

***Index Terms*: Beamforming optimization, BAT algorithm, Massive MIMO, Millimeter-wave**

I. Introduction

The rapid increase in the number of users and demand for better quality-of-service is the major reason which requires newly proposed standards in wireless communications. The 5th generation wireless systems are referred to as an ideal fit to meet business and consumer demands. Considering the scenarios and use-cases, fifth-generation (5G) Mobile Networks Alliance requires some basic requirements [1-6].

1) Huge high data rates
2) Very low latency rate
3) Large capacity for the number of connected devices
4) High reliability

All of these requirements have initiated the motivation to explore the underutilized frequency spectrum of millimeter waves (mmWave) for deployment in the future networks of broadband cellular communication networks [2]. Millimeter-Wave utilizes the frequency spectrum ranges from 30 GHz to 300 GHz. The capacity of wireless communication networks is increasing exponentially. This rapid rise is the result of increasing demands for high-speed data transfer. The most recent 5G networks claim the ability to bring about 1000 times expansion in the capacity by the year of 2020 [3]. One possible way to enhance capacity is to increase spectral efficiency, which includes methods having massive MIMO (multiple inputs multiple outputs) and advanced channel coding schemes [4]. Area spectral efficiency can be further improved by network densification, for example by permitting device-to-device (D2D) communications [5], or by deploying small cells [6] [7] also by enabling advanced cooperation, such as Cloud Radio Access Networks (RANs) [8-9]. This makes it essential to exploit the spectrum bands which are underutilized. These are the bands which are under no usage of any cellular communications by 2020 [3].

Millimeter-wave operates on a minimum 30 GHz to maximum of 300 GHz bands. These waves had previously been used only for the purpose of carrying the indoor high-resolution multimedia streams [10] or any point-to-point backhaul links in the outdoors [11]. Hence mmWave are the most feasible option for the application of outdoor cellular communications which is now backed up by some experimental proofs as well [12-16].

The basic obstacles in mmWave systems include the great amount of path loss and the attenuation caused by rain. These obstacles arise because the carrier frequency increases by ten-fold [2]. Since mmWave MIMO has small wavelengths, therefore precoding techniques provide significant beamforming gains that efficiently tackle this path loss caused at the transceiver's antennas.

In traditional MIMO systems, precoding takes place at baseband level using digital precoders scheme. This scheme helps to adjust the signal magnitude as well as the signal phase. On the other hand, to perform fully digital precoding it requires the RF chains and analog-to-digital converter (ADCs).

Recently, a hybrid precoding architecture has emerged, which involves a few RF chains. The high dimensional analog and a low dimensional digital precoder are interfaced with RF chains [14-18]. The high dimensionality of analog precoders renders it not suitable for use in RF domain that utilizes variable voltage amplifiers (VGA) with very high power [2], whereas they can still be used alongside the more economical phase shifters.

The considerable reason for the increment of interest in research works for mmWave is that the bandwidth of the mmWave spectrum is very large compared to the bandwidth of the spectrum used by fourth-generation (4G) and older wireless network technologies. Since these mmWave frequencies have a very small wavelength, therefore, they exploit polarization well along with other novel spatial processing techniques, including adaptive beamforming as well as massive MIMO [15].

In standard MIMO systems, each antenna element is directly connected to the baseband processor. This requires a dedicated mixer, an ADC or a digital-to-analog converter (DAC), filters and amplifiers per antenna. The basic purpose of beamforming is to direct signal transmission and reception. Beamforming basically steers the signal in a particular direction. Its elemental principle is to change the amplitude and phase of the signal for power variation and beam steering.

In analog beamforming, the signal's phase and amplitude variation are activated along with the analog signal at transmitting end whereas in digital beamforming the signal's phase and amplitude are varied along with the digital signal before DAC at the transmitter end. The received signals coming out of antennas are first fed into the ADC converters and digital down converters (DDCs) before summation operation. Analog Beamforming is typically preferred by the mmWave massive MIMO. The direction of the steering signal at both ends i.e.at transmitter and receiver end is monitored using the analog phase shifter (PS) network which is considered to have very low hardware cost [2]. Existing dominant analog beamforming schemes are generally branched into two groups of codebook-based beamforming and another group is the non-codebook-based beamforming. This CSI is effectively a collection of the spatial transfer functions between each user terminal and each antenna but the collection of the CSI is quite a difficult task to do, chiefly when their isa limited count of RF chains [2]. It can achieve the optimal and best combination of analog precoder that can be found by searching in the predefined codebooks. On the downside, in order to successfully transfer the information between the BS and user, the systems require a large number of iterations. Furthermore, complexity increases exponentially with the increase in quantified bits along with the angles of arrival as well as angles of departure (AoA/ AoDs) and the total number of RF chains [16]. In this work, an optimized scheme for beamforming is proposed which searches for the optimized combination of analog precoder/ combiner to attain the best performance with low complexity.

II. Modified BAT Algorithm for Optimizing beamforming in Mmwave Massive MIMO Systems

Metaheuristic algorithms such as the very common ones particle swarm algorithm PSO, genetic algorithm (GA) are high-level problem-independent algorithms [43-44]. They are basically stochastic algorithms with the capability to perform local search and randomization. The two major composing elements for metaheuristic algorithms are regarded as the randomization and selecting the fittest. The process to select the fittest makes sure that all the selected solutions converge to the optimum solution, whereas randomization ensures global uniqueness and prevents the solution from being trapped in local optimum [17-19]. Reason for such success is their quality of being tolerant of non-differentiable as well as non-convex search spaces in addition to obtaining acceptable solutions in a feasible practical time [20]. Most of the techniques of metaheuristic algorithms have been inspired by nature like animals, plants, natural phenomena, and laws, etc. The objective of nature-inspired algorithms is to extract and attain the finest features in nature and then design them effectively using different mathematical operators. These kind of optimization algorithms been widely used in solving numerous research problems in the area of communications and security [45-46].

Primarily the performance and efficiency of algorithms, which are nature-inspired, banks on the balance between exploitation and exploration. Exploration is referred to a process to search the space globally and the process of exploitation is referred to search the space locally considering the given best solutions. To achieve the global optimality there should be a good balance between these two [21].

The authors in [22] propose a scheme based on the echolocation property of bats. These pulses have varying rates of emission and pulse loudness. This nature-inspired algorithm scheme has been used in different applications [23]. However, BA has a possibility to stuck in local optima, therefore, it is important to improve its convergence performance [21]. The major two shortcomings of Bat Algorithm are:

1. The original algorithm fails to depict the bats' self-adaptive capability in true sense which they have with respect to surroundings. Studies explain how bats can discriminate their targets by slightly changing the Doppler effect that is caused due to wing-flutter rates of their target insects [24].
2. The other is that the formulae of the Bat Algorithm do not clarify the balance between exploitation and exploration.

In our research, we used an improved and modified version of the bat algorithm, namely Novel Bat Algorithm (NBA), which better reflects the bats' characteristics. It was devised by Xian-Bing Meng et al [25] in 2015.

The performance of the NBA is far better compared to that of typical Bat Algorithm because it replicates the behavior of bats more ideally, hence enhancing optimization results. The proposed algorithm integrates into the basic BA and helps in compensation for Doppler effect in echoes and their habitat selection. Moreover, the NBA simulates the echolocation characteristics of bats are more precisely. A local search strategy is the main feature of the NBA in which the BAT adapt themselves which leads to enhancing the results to a further degree.

Pseudo Code for NBA:

Algorithm 1: NBA

Inputs:
N: The total population (No. of individuals)
M: The total No. of iterations
P: Probability for habitat selection
C: Doppler Effect rates for echo compensation
θ: Coefficient of Constraint Expansion
G: Frequency of pulse emission as well as loudness
W: Presents Inertia (weight)
r_i original BA parameters
 	
t=0; Initialize population corresponding parameters.
Assess the value of each bat-solution of the objective function.
 	
While $(t < M)$
Generate new solutions
If (rand (0,1) > r_i)
For the given best solution, a local solution is generated,
End if
For each value of the objective function for each individual Solutions, an objective function is evaluated; also the loudness as well as pulse emission rate are updated
Find the current best g^t by ranking the solutions and
If g^t shows no improvement in the time step of G.
Reinitialize the loudness variable A_i. Also the set of temporary pulse rate r_i is set. Here r_i presents a uniform random number [0.85 , 0.9]
End
t=t+1;
End

Results:

The individual from the total population having the best objective function value.

III. SYSTEM MODEL

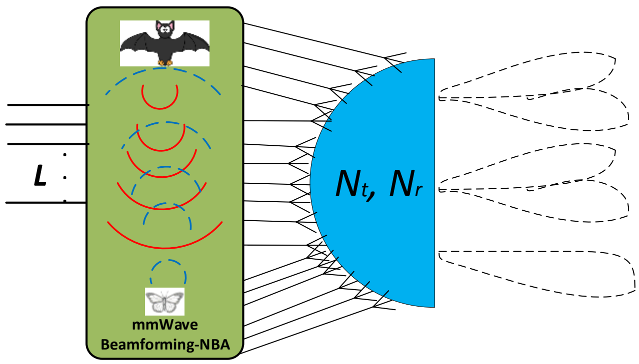

Figure 1 MmWave MIMO transmitter architecture

Here, the system model of our proposed method is presented and discussed. For the reference of our readers, Fig. 1 demonstrates the architecture of mmWave MIMO transmitter that we have adopted in our designed system to maintain the transceiver antennas used in our simulation. We have considered in this work beamforming via massive MIMO system which is depicted in Fig 2 for transmitter and Fig. 3 for the receiver. The BS has a total of $\boldsymbol{N_t}$ antennas with $\boldsymbol{N_t^{RF}}$ RF chains. Using these $\boldsymbol{N_s}$ number of data streams, data are simultaneously transmitted to a user that has $\boldsymbol{N_r}$ antennas and $\boldsymbol{N_r^{RF}}$ RF chains. In order to gets full spatial multiplexing gain, we have [23]:

$$\boldsymbol{N_t^{RF}}=\boldsymbol{N_r^{RF}}=\boldsymbol{N_s} \tag{1}$$

The $\boldsymbol{N_s}$, which represents data streams in eq.1, are first converted into baseband by passing through $\boldsymbol{N_t^{RF}}$ RF chains which converts them into analog signals. In the next step the output signals by an $\boldsymbol{N_t} \times \boldsymbol{N_t^{RF}}$ analog precoder $\boldsymbol{P_A}$ will be pre-coded as **x** = $\boldsymbol{P_A s}$, where '**s**' shows the $N_s \times 1$ number of vectors of the transmitted signal with the normalized value of power as $E(\boldsymbol{ss^H}) = \frac{\boldsymbol{1}}{\boldsymbol{N_s}}\boldsymbol{I_{N_s}}$.

All the elements of the analog precoder should satisfy $\left|\boldsymbol{p_{i,j}^A}\right|^{\boldsymbol{2}} = \frac{\boldsymbol{1}}{\boldsymbol{N_t}}$ [25] . In case othe f narrowband block-fading massive MIMO channel [14], if $\boldsymbol{r}$ is the $N_r \times 1$ received signal vector, then [23]:

$$\boldsymbol{r} = \sqrt{\rho} H P_A \boldsymbol{s} + n \tag{2}$$

Here ρ represents the power that is transmitted and **H**∈ □$^{N_r \times N_t}$ denotes the channel matrix, , and n = [n1, · · ·, nNr]^T is the AWGN noise vector with $CN(0, \sigma^2 \mathrm{I}_{N_r})$. At the other end, an $N_r \times N_r^{RF}$ analog combiner C_A processes the signal vector $\boldsymbol{r}$ at the receiving end as [23]:

$$\boldsymbol{y} = C_A^H \boldsymbol{r} = \sqrt{\rho} C_A^H H P_A \boldsymbol{s} + C_A^H \boldsymbol{n} \tag{3}$$

where the elements of C_A have identical constraints similar to that of P_A, i.e., $CN(0, \sigma^2 \mathrm{I}_{N_r})$.

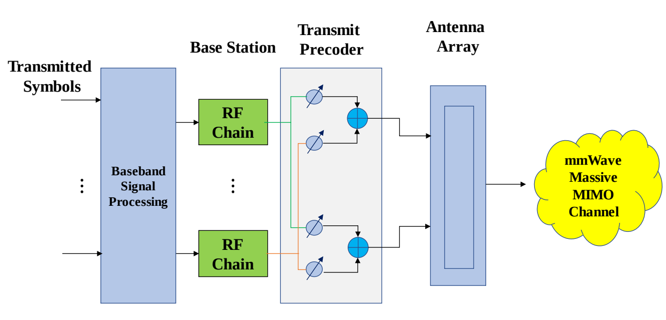

Figure 2 Beamforming of Massive MIMO at the Transmitting end

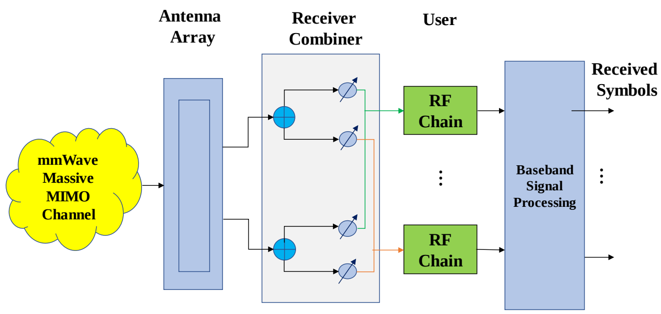

Figure 3 Beamforming of Massive MIMO at the Receiving end.

IV. Methodology

In this section, the methodological steps that were applied to conduct our study presented in details. Fig. 4 shows the

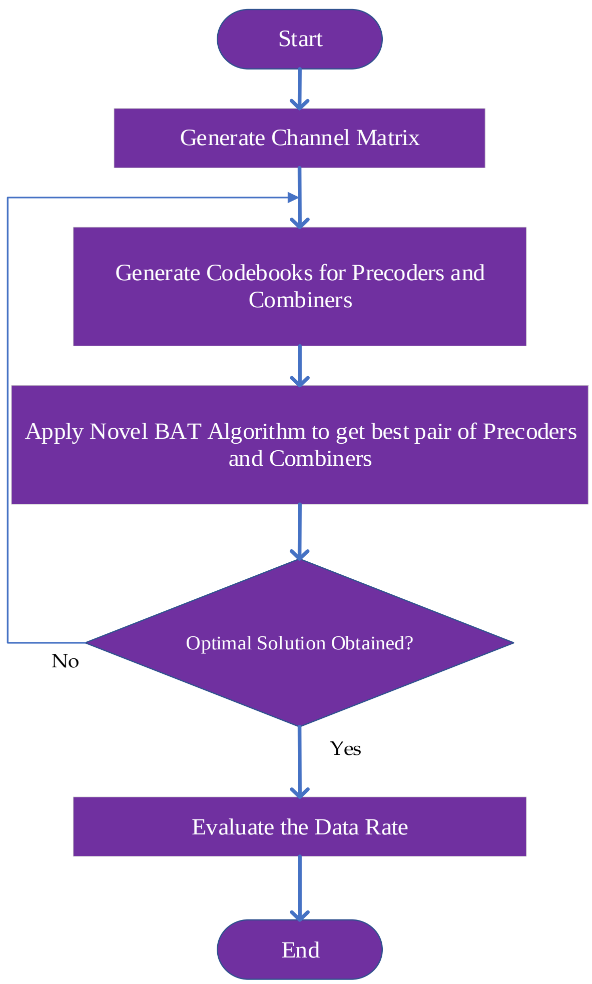

Figure 4 Flow Diagram for this research work.

A. Channel Simulations

The initial step in the process of simulation is the generation of a channel for transmission. In our simulation, we have considered the geometric model of channel in order to carry out the modeling of the propagation environment, as there is the very finite number of significant scatters ($L \le \min(\mathrm{N}_t, \mathrm{N}_r)$) and there exists genuine antenna correlation in mmWave systems [28], so we choose the widely popular geometric Saleh-Valenzuela channel model [29]. Saleh and Valenzuela in their work explained the clustered characteristic in the indoor environment of measured received power delay profiles. The statistical model proposed by them is an extension of the well-known Turin model. The Saleh and Valenzuela channel matrix represented by **H** is as follows [23]:

$$H = \sqrt{\frac{N_t N_r}{L}} \sum_{l=1}^{L} \alpha_l f_r(\phi_l^r) \mathrm{f}_t^H(\phi_l^t) \tag{4}$$

Here $\alpha_l \in \mathbb{C}$ presents the net gain of the lth path. ϕ_l^t and ϕ_l^r represents the azimuth of lth path AoDs/AoAs. $f_t(\phi_l^t)$ and $f_r(\phi_l^r)$ are the response vectors of the antenna arrays which are highly dependent upon the structure of the antenna array employed both at BS as well as user ends. With uniform structure e of linear arrays (ULAs), it follows as [23]:

$$f_t(\phi_l^t) = \frac{1}{\sqrt{N_t}}\left[1, e^{jkd\sin(\phi_l^t)}, \cdots, e^{j(\mathrm{N}_t-1)kd\sin(\phi_l^t)}\right]^T \tag{5}$$

$$f_r(\phi_l^r) = \frac{1}{\sqrt{N_r}}\left[1, e^{jkd\sin(\phi_l^r)}, \cdots, e^{j(\mathrm{N}_r-1)kd\sin(\phi_l^r)}\right]^T \tag{6}$$

Here

$k = \frac{2\pi}{\lambda}$,

λ is the signal wavelength while d denotes the spacing in antennas.

B. Generation of Codebooks

Codebooks can be considered as a matrix where the columns are termed as the beamforming weight vector and also give them information about the pattern or the direction of beams. The columns set extends along with entire space. In order to support beamforming both 1-D phased antenna and 2-D phased antenna is utilized. These codebook matrices are generated in a symmetric order and they create a near-circle pattern for minimum gain loss along the intersecting boundaries of the two adjacent patterns as shown in Fig. 5.

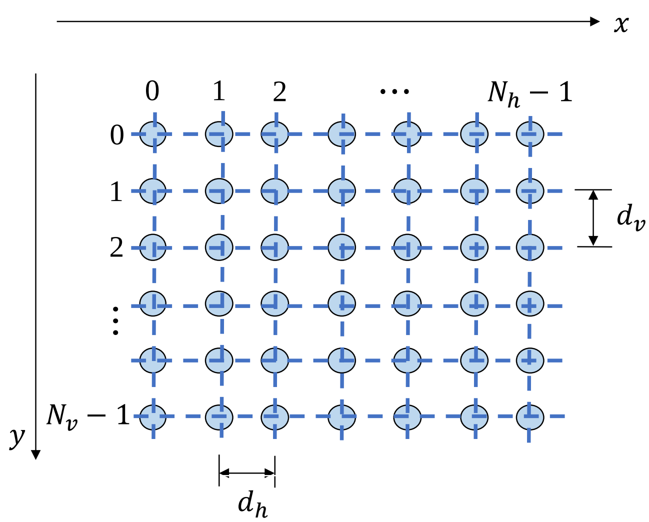

Fig. 5. Generation of the codebook.

The beam steering codebook [30] is broadly used since it presents special characteristics of the mmWave channel. Suppose F represents the beam steering codebook for analog precoder and contains all possible analog precoder matrices (PA). W represents the beam steering codebook for analog combiner and contains all possible analog combiner matrices (CA). B_t^{RF} (B_r^{RF}) represents the number of bits to compute AoD (AoA). Each precoder and combiner matrix will be of the form [23]:

$$P_A = \left[f_t(\bar{\phi}_1^t), f_t(\bar{\phi}_2^t), \cdots, f_t(\bar{\phi}_{N_t^{RF}}^t)\right] \quad (7)$$
$$C_A = \left[f_r(\bar{\phi}_1^r), f_r(\bar{\phi}_2^r), \cdots, f_r(\bar{\phi}_{N_r^{RF}}^r)\right] \quad (8)$$

where the computed AoD $\bar{\phi}_i^t$ for i = 1, · · ·,N_t^{RF} at BS has $2^{B_t^{RF}}$ possible candidates, i.e. $\bar{\phi}_i^t = \frac{2\pi n}{2^{B_t^{RF}}}$ where n ∈ {1, · · · $2^{B_t^{RF}}$}. Also, the computed AoA $\bar{\phi}_j^r$ for j = 1, · · ·, N_r^{RF} at user has the $2^{B_r^{RF}}$ possible candidates, i.e., $\bar{\phi}_j^r = \frac{2\pi n}{2^{B_r^{RF}}}$ where n ∈ {1, · · · $2^{B_r^{RF}}$}. Therefore, |F| of F and |W| of W cardinalities are $2^{B_t^{RF}.N_t^{RF}}$ and $2^{B_r^{RF}.N_r^{RF}}$, respectively.

C. Definition of Cost Function

By combinational search for all possible pairs of *F* and *W*, the selection of the finest combination of the analog combiner and analog precoder can be done on the basis of the maximization of the achievable rate R is represented as [23]:

$$R = \max_{P_A \in F, C_A \in W} \log_2\left(\left|I_{N_s} + \frac{\rho}{N_s} R_n^{-1} C_A^H H P_A P_A^H H^H C_A\right|\right) \quad (9)$$
$$R = \max_{P_A \in F, C_A \in W} \log_2(\varphi(P_A, C_A)) \quad (10)$$

where $R_n = \sigma^2 C_A^H C_A$ represents the covariance matrix of the noise after combining. So, the final equation of achievable rate can be written as [23]:

$$\varphi(P_A, C_A) = \left|I_{N_s} + \frac{\rho}{N_s} R_n^{-1} C_A^H H P_A P_A^H H^H C_A\right| \quad (11)$$

Thus, the purpose of optimization, which is discussed in the next topics, is to maximize the above-mentioned achievable rate.

D. NBA Optimization of Precoder and Combiner indices to be selected

In order to maximize the amount of achievable rate, an optimal combination of the precoder and combiner must be selected from all possible combinations. For this objective, an improved approach to the Bat Algorithm which was proposed in [25] was used. In this portion, an overview of the classic Bat Algorithm is given first. After that, an explanation of the modifications has presented that lead to the improved results that mimic Bat behavior more closely.

The basic principle for Bat Algorithm is that *n* number of bats flies in a random fashion using echolocation to sense distances through a *d* dimensional space. Some approximations, as well as some idealized rules proposed by Yang, are as follows:

Idealized Rule 1:
All bats possess the ability to sense distance by using their feature of echolocation. Also, they can, by using this property, differentiate between their target prey as well as the background.

Idealized Rule 2:
Bats use to fly randomly with the velocity vi at position $x_i = [xi_1, xi_2, xi_3, ..., x_{id}]$ with a fixed frequency f_{min}. However, they can change the wavelength λ and loudness A0 in order to find their prey. Bats have the ability to change and adapt the wavelength of the pulses they emit, according to the distance between them and their targets.

Idealized Rule 3:
Various steps involved in the Bat Algorithm [22] are as follows:

1) Initialization
The N bats (solutions where every solution is the possible combination of the analog precoder and combiner) specified by the positions xi and the velocities vi are distributed randomly in a feasible search space having a D-dimension. The N bat velocities might be set to zero.

$$x_{i.j} = x_{jMin} + (x_{jMax} - x_{jMin}) * \text{rand } (0,1),$$

Where $i \in [1, \ldots, N]$, $j \in [1, \ldots D]$.

2) Create new bats

$$f_i = f_{\min} + (f_{\max} - f_{\min}) \times \beta,$$
$$v_i^{t+1} = v_i^t + (x_i^t - x_*) \times f_i,$$
$$x_i^{t+1} = x_i^t + v_i^{t+1},$$

Here $\beta \in [0,1]$ presents a random vector. The frequencies f_{max} and f_{min} depends on the size of the domain of the given problem.

3) Local search

$$if\,(rand(0,1) > \mathrm{r}_i)$$
$$\mathrm{x}_{new} = \varepsilon A_{mean}^t + x_{old}$$

Here $\varepsilon \in [-1,1]$ presents the random value from the uniform distribution, "A_t" is regarded as the mean average value of loudness for all the bats at the time step t. $r_i \in [0,1]$.

4) Bat update upon random flying
The decrease in loudness and an increase in the rate of pulse emission follows the following equations

$$if\,(rand(0,1) < A_i \& f(x_i) < f(x))$$
$$A_i^{t+1} = \alpha A_i^t,$$
$$f(x) = f(x_i),$$
$$r_i^{t+1} = r_i^0(1 - e^{-\gamma t})$$

Where the constants are $\alpha(\alpha \in [0,1])$ and $\gamma(\gamma > 0)$.

5) Updating the solution of the current global best
Finally, the best current global solution is updated before moving on to the next iteration.
The following two points make NBA different from traditional Bat Algorithm as it depends on the stochastic selection where all the bats can hunt in individual habitats. Also, all the bats can recover from the Doppler effect that is caused in echoes. In addition, the bats can change the rate of compensation with respect to the target's closeness.
Most of the bats have the unique and state of the art ability to use sound pulse having a constant frequency for echolocation Whereas some bats use signals that are frequency modulated. The bats use these pulses to hunt down their preys. In addition, the bats can detect their prey, avert the obstructions and find the roosting crevices in the dark [22]. Having the advanced ability of echolocation, the bats can easily recognize the orientation and distance of their prey. In addition, Bats can also vary their sound pulses frequencies and search behavior while they search in different type of habitats [31]. Different bats' species search in different habitats like forests, water environments, etc [32]. Different bat species can also search in the same habitat [33].

Different species of bats have different searching habitats. In BA, each bat searches for its prey from a different position and with different velocity in a given D-dimensional space. The region for the motion of bats is limited to the finite zone according to the bound state constraint. Therefore, in typical BA, the bats can search only in a single habitat, unlike in NBA. Some of the species have the ability to compensate the partial Doppler's effect encountered in the echoes, some species are able to show near to full compensation [34]. The original Bat Algorithm, however, did not consider the effects caused by the Doppler effect.

V. Simulation Results

We used MATLAB to experimentally analyze the proposed work. We compare our work with two recent relevant benchmarks from literature: The upper limit of the proposed beamforming scheme with quantified AoA/AoDs [33] with continuous angles and the scheme in [18]. Both the transmit and receive antennas are considered to be Uniform Linear Arrays (ULAs). The parameters set for the system used for simulation are:

- The carrier frequency is 28GHz.

- Scattering propagation paths (L) is fixed to be 3.
- Antenna spacing (d) is kept to be π /2.
- $N_t^{RF} = N_r^{RF} = N_s = 2$
- The AoAs/AoDs used to generate the channel matrix from [27] are assumed that they pursue the uniform distribution in the limits of [0, π]. The standard deviation of the angles in azimuth and elevation both of Rx and Tx is kept to be 10/180* π. αl is the complex gain of the lth path which follows αl ∼ CN (0, 1). SNR is given as ρ / σ^2
- Wavelength is kept to be 2 mm.

Simulation results are evaluated at three different cases based on quantized bits per AoAs/AoDs which are enlisted as follows:

- $B_t^{RF} = B_r^{RF} = 4$
- $B_t^{RF} = B_r^{RF} = 5$
- $B_t^{RF} = B_r^{RF} = 6$

The basic purpose of the NBA here is to select the optimum pair of indices of F and W codebooks. The selected index of F codebook selects a possible analog precoder and the selected index of W selects a possible analog combiner. The goal is to come across such a pair of these two indices such that achievable rate is maximized.

The parameters of the basic Bat Algorithm (BA) that we used in the NBA are given in Table 1, while Table 2 lists some additional parameter sets of NBA algorithm.

Table 1 Parameters for BAT Algorithm

Parameters	Values
Number of iterations	100
Population size	30
The factor of the speed of increase (gamma)	0.9
The factor of the speed of increase (alpha)	0.9
Maximum pulse rate	1
Minimum pulse rate	0
Maximum loudness	2
Minimum loudness	1
Maximum frequency	0.5
Minimum frequency	0
Emission rate	10
The maximal and minimal probability of habitat selection	0.9
The minimal probability of habitat selection	0.6
The maximal contraction expansion coefficient	1
The minimal contraction expansion coefficient	0.5
The maximal inertia weight	0.9
The minimal inertia weight	0.5
The maximal compensation rate for echo-Doppler effect	0.9
The minimal compensation rate for echo-Doppler effect	0.1
The maximal and minimal probability of habitat selection	0.9

Table 2 The additional parameters in Novel Bat Algorithm (NBA)

Parameters	Values
The frequency for updating loudness and pulse emission rate	10
Maximal/ minimal probability of habitat selection	0.9
The minimal probability of habitat selection	0.6
The maximal contraction expansion coefficient	1
The minimal contraction expansion coefficient	0.5
The maximal inertia weight	0.9
The minimal inertia weight	0.5
The maximal compensation rate for echo-Doppler effect	0.5
The minimal compensation rate for echo-Doppler effect	1

Turbo T_s beamforming [18-20] has been shown to give near-optimum results in reaching the benchmark of the recently proposed beam steering [35-42] with continuous angles.

According to the Simulation results, the proposed NBA scheme gives much better results than its turbo TS counterpart.
In Figure 6, the results of the proposed method for the case is presented, where Nr= 16 and Nt= 64. Figure 7 shows results for the case where Nr= 32 and Nt= 128.

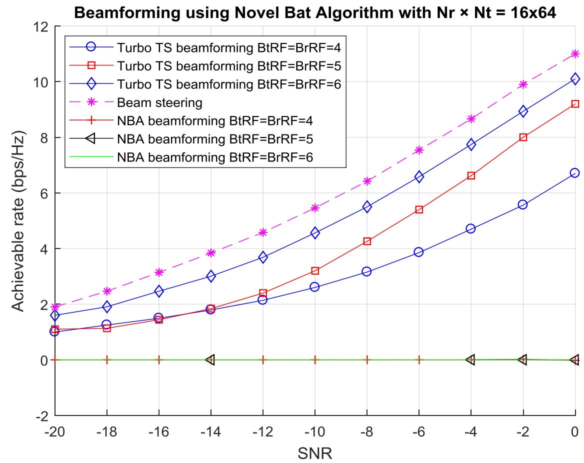

Fig. 6 Beamforming using BAT Algorithm NrxNt=16x64

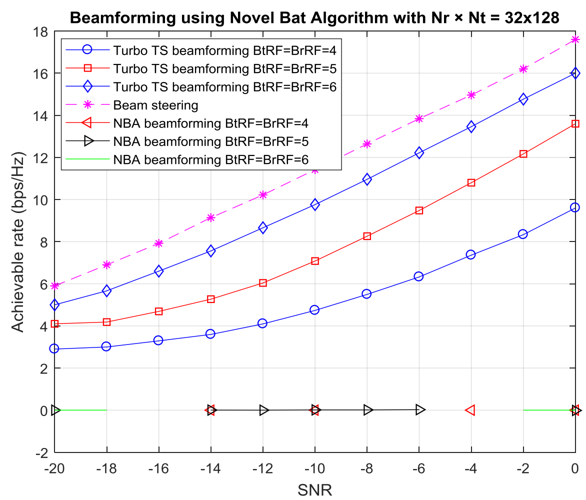

Fig. 7. Beamforming using BAT Algorithm NrxNt=32x128

In Fig. 6, the achievable rate for $N_r \times N_t = 16 \times 64$ with

$$N_t^{RF} = N_r^{RF} = N_s = 2$$

Fig. 7 depicts the comparison of achievable rate Nr × Nt = 32 × 128. In this case, the amount of RF chains is

$$N_t^{RF} = N_r^{RF} = N_s = 2$$

Figures 6 and 7 shows that the performance of NBA beamforming (like that of Turbo TS beamforming) improves as the total number of quantified bits per AoAs and AoDs is increased. NBA outperforms Turbo TS and approaches the results of beam steering method much more closely. In addition, we found that in order to enhance the performance of the proposed NBA beamforming scheme, the number of antennas should be incremented rather than incrementing the number of RF chains. This improvement is much more pronounced for NBA than it was for Turbo TS. It can have a profound effect on reducing the overall cost of the system.

VI. Conclusion

In this research, we proposed the use of Novel Bat Algorithm (NBA) to choose the best combination of analog precoder and combiner to achieve wireless communication in a mmWave massive MIMO channel. First, the codebooks were generated for analog precoder and combiner. Then out of those codebooks, the most optimum pair for analog precoder and combiner was selected via Novel Bat Algorithm. It is concluded from the simulation results that the proposed approach is superior to the Turbo TS scheme, in terms of the achievable rate, yielding results that are closer to the beam steering benchmark. The proposed method's advantages are two-fold. Firstly, the NBA optimization scheme has a self-adaptive capability. Possible solutions- which are the possible combinations of precoder and combiner matrices from the F and W codebooks- imitate bats as they can adaptively recover the changes due to the Doppler effect in echoes. As for the local search, the algorithm to update solutions is self-adaptive and does not involve any parameters defined by the user. Similarly, this optimization method combines optimal diversity with efficient convergence capabilities. Considering the methodology of the bats' habitat selection, the solution diversity for this algorithm can be increased by employing two different search strategies. Current work was based on ULAs and for a single user scenario. In the future work can explore the domain of UPAs (uniform planar arrays) [24] and also extend it to multiple user domains. Furthermore, other channels of Massive MIMO [34] [35] can be analyzed and compared.

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